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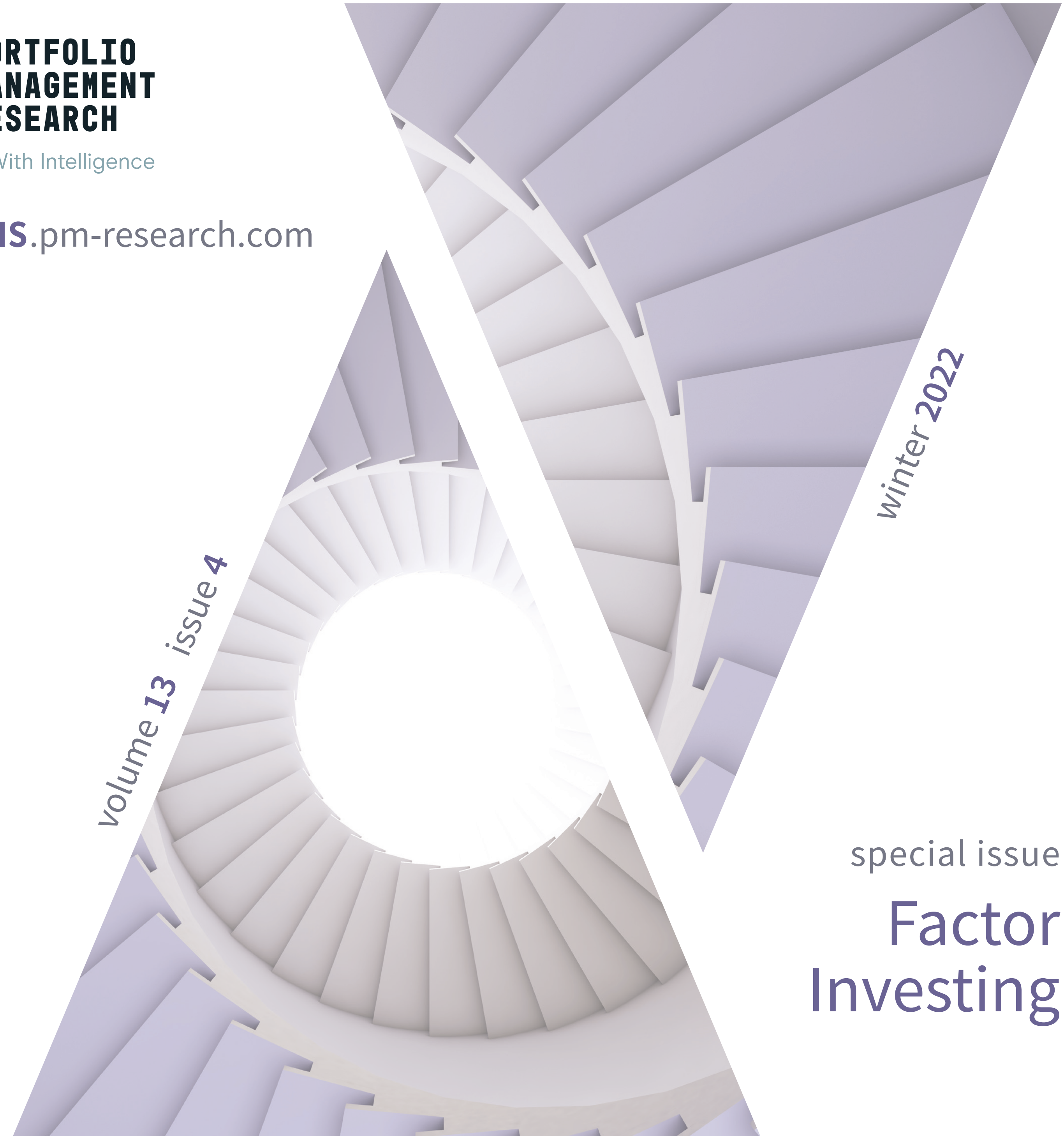

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Factor Investing

Measuring Sector Cyclicality: A Factor-Based Approach

Alessio de Longis, Daniel Zanin, and Dianne Ellis

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Measuring Sector Cyclicality: A Factor-Based Approach

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KEY FINDINGS

- Sector sensitivities to the economic cycle change over time in line with changes in underlying fundamental factor exposures.
- Factor cyclicality can be used to quantify sector economic exposures more dynamically than static classifications used in the industry.
- A factor-based approach to sector classification can support the development of traditional sector rotation strategies with attractive excess returns and improved results versus static classification alternatives.

ABSTRACT

Equity sectors are often ascribed static economic classifications that fail to consider their dynamic and time-varying fundamental characteristics across business cycles. Leveraging research findings on factor cyclicality, the authors propose a simple and practical methodology to categorize sectors as cyclical or defensive by estimating their sensitivity to a cyclical multifactor portfolio. Their results reveal that although some sectors have exhibited persistent cyclical or defensive features, most sectors have experienced noteworthy changes over time. Using a predictive business cycle regime framework, they document the effectiveness of this dynamic factor-based sector classification approach and provide examples of sector rotation strategies that have historically generated attractive excess returns, outperforming static alternatives. Their results are consistent with a factor investing paradigm, recognizing that factors are important drivers of portfolio risk and performance, and traditional asset classes can be seen as implementation vehicles of intended factor and macro exposures.

The use of characteristic-based factor models took hold in academia with the seminal publication of Fama and French (1993), which evolved the Sharpe (1964) capital asset pricing model (CAPM) into a three-factor model of stock returns, thereby capturing the incremental effects of the size and value premium. Since then, a rapid transformation has taken place in the asset management industry, as both academics and investment professionals have documented that quantitative stock characteristics, or factors, are associated with long-term risk premiums and explain the cross-sectional variation in stock returns (e.g., Carhart 1997; Fama and French 2015, 2018; Frazzini and Pedersen 2014). This new factor investing paradigm is founded on the explicit recognition that factors are important drivers of portfolio risk and performance, representing more-relevant characteristics of a security than its country, sector, or industry classification. Hence, factors should influence asset allocation decisions, and traditional asset classes can be seen as baskets of securities that serve as simple implementation vehicles to achieve intended macro exposures (see also Melas 2022 and Swade et al. 2022 for conceptual and empirical examples).

Alongside the rise of factor investing, however, sector-based investing remains one of the oldest and most popular disciplines in the investment industry. Financial news is still dominated by sector/industry stories, and investment research functions across banks and asset managers are primarily organized along sector lines, as sectors provide reasonable benchmarks to evaluate the performance of individual companies relative to peers. Research shows that global sector and industry effects have played a larger role than country effects in the cross section of portfolio returns since the late 1990s (Held 2009; Cavaglia et al. 2000; Cavaglia and Moroz 2002). Consequently, a large body of research has focused on the merits of strategic and tactical sector rotation strategies, documenting momentum effects (Doeswijk and Van Vliet 2011), valuation effects (Bunn et al. 2014), and the influence of macro factors (Chong and Phillips 2015; Canover et al. 2008). Although it is understood that a large dispersion in sector returns reflects different sensitivities to the economic cycle, there is no widely adopted standard in the asset management industry to determine whether a sector is cyclical or defensive. Index and research providers offer different perspectives on sector cyclicality, and sector classifications tend to be static over time. From a theoretical standpoint, this vacuum can be justified because sectors and industries represent a risk factor, not a return factor, and investors should not expect to earn a long-term risk premium over the market based on the sector classification of a security.

In this article, we argue that a factor allocation framework can shed light on sector sensitivity to the economic cycle and that factor cyclicality can be exploited to describe sector behavior in a more dynamic fashion compared with static cyclical/defensive classifications. We contribute to the literature on sector and factor investing in two ways.[1] First, we propose a simple and practical methodology to dynamically classify sectors as cyclical or defensive by estimating their empirical sensitivity to a cyclical multifactor portfolio using easily accessible factor indices. Second, we illustrate how traditional macro regime frameworks used to develop dynamic factor rotation and tactical asset allocation strategies can be similarly deployed toward sector rotation strategies using market-capitalization-weighted sector indexes, easily accessible via index funds or exchange-traded funds (ETFs).

The article is structured as follows. The first section outlines the motivation of this study, providing examples of sector classification methodologies in the industry and a brief review of the literature on factor cyclicality. The second section describes the methodology and data. The third section reports results, and the fourth section illustrates a practical investment application. The final section concludes, offering thoughts for future research.

MOTIVATION

Motivated by different quantitative and qualitative inputs to their methodologies, index and research providers offer different conclusions on sector cyclicality. As an illustrative example, Exhibit 1 summarizes MSCI and Morningstar sector groupings by economic sensitivity, with MSCI defining two broad categories, cyclical and defensive, and Morningstar defining three super sectors, including a “sensitive” super sector as a separate category, in between cyclical and defensive. In both instances, these economic classifications have been structural in nature and static since their release.[2]

[1] For recent studies on the interaction between sector and factor investing, see Vyas and van Baren (2021) and Bessler, Taushanov, and Wolff (2021).

[2] MSCI cyclical/defensive sector indexes group the Global Industry Classification Standard (GICS®) sectors based on their long-run historical correlation with the economic cycle (MSCI 2009), and these categories have remained unchanged since their release in 2014. Similarly, Morningstar groups sectors into three super sectors—cyclical, defensive, and sensitive—reflecting industries with a market beta of greater than 1, less than 1, or close to 1, respectively (Morningstar 2011).

EXHIBIT 1

Examples of Sector Classification by Economic Sensitivity

	Classification	
GICS® Sectors	**MSCI**	**Morningstar**
Consumer Discretionary	Cyclical	Cyclical
Consumer Staples	Defensive	Defensive
Energy	Defensive	Sensitive
Financials	Cyclical	Cyclical
Health Care	Defensive	Defensive
Industrials	Cyclical	Sensitive
Information Technology	Cyclical	Sensitive
Materials	Cyclical	Cyclical
Real Estate	Cyclical	Cyclical
Communication Services	Cyclical	Sensitive
Utilities	Defensive	Defensive

NOTES: Morningstar sectors have been adapted to GICS® sector terminology. Consumer cyclicals, consumer defensives, and technology have been respectively paired to consumer discretionary, consumer staples, and information technology.

SOURCES: MSCI (2014, 2018) and Morningstar (2011).

EXHIBIT 2

Factor-Based Economic Classification of Sectors

Sector Classification	β	p-Value	Economic Interpretation
Cyclical	> 0	≤ 0.1	Excess returns are positively correlated with cyclical factors
Neutral	any	> 0.1	Excess returns are uncorrelated with cyclical factors
Defensive	< 0	≤ 0.1	Excess returns are negatively correlated with cyclical factors

NOTE: A p-value of ≤ 0.1 denotes significance with a 90% confidence interval or higher.

A few differences stand out, with industrials, communication services, and information technology classified as "cyclical" by MSCI and "sensitive" by Morningstar. Energy is classified as "defensive" by MSCI and "sensitive" by Morningstar.

A factor allocation framework can shed light on these differences and provide useful tools to understand sector cyclicality and risk. Fundamental factors such as value, size, quality, low volatility, and momentum represent more-precise quantitative characteristics of a security, with associated premiums over the long term. Academic and industry research has documented the cyclicality of equity factors, which can be understood in the context of factor sensitivity to aggregate cashflow news. Campbell and Vuolteenaho (2004), Campbell, Polk, and Vuolteenaho (2010), and Campbell et al. (2018) document substantial heterogeneity in factor exposure to aggregate cash-flow news, linked to fundamental characteristics such as profitability and operating leverage. Polk, Haghbin, and de Longis (2020) document how value and small size tend to be cyclical, holding relatively large cash-flow betas, while strategies such as low-volatility and quality hold relatively low cash-flow betas and exhibit defensive behavior.[3] These differences in economic sensitivity are statistically significant and, importantly, do not simply reflect differences in market beta.[4]

METHODOLOGY AND DATA

Building on Polk, Haghbin, and de Longis (2020), we define sector cyclicality based on each sector's sensitivity to a cyclical factor portfolio (CFP). This factor portfolio is long cyclical, high cash-flow beta factors (value and size) and short defensive, low cash-flow beta factors (quality and low volatility). For each S&P 500 GICS® sector, we estimate 10-year rolling univariate regressions:

$$S_t = \alpha + \beta * CFP_t + \varepsilon_t$$

where S_t refers to the GICS® sector excess returns over the market-cap index (S&P 500), CFP_t refers to returns of the cyclical factor portfolio, defined as the return difference between a "value & size" portfolio and a "low volatility & quality" portfolio, and ε_t is the error term. On a monthly basis, we classify sectors as cyclical, defensive, or neutral based on the sensitivity and significance rules outlined in Exhibit 2.

[3] The authors further illustrate how investors can use insights on the future state of the economy (recovery, expansion, slowdown, and contraction) to tilt portfolio exposures toward factors expected to outperform in each macro regime.

[4] Momentum, consistent with the transitory price-based nature of its signal, exhibits a less persistent exposure to cash-flow news, and tends to exhibit a higher cash-flow beta in expansions and a lower cash-flow beta in contractions.

EXHIBIT 3
FTSE Russell Multifactor Indexes

	Value	Size	Quality	Low Volatility	Momentum
Cyclical Factor Portfolio	2	2	0	0	0
Defensive Factor Portfolio	0	0	2	2	0
Russell 1000 Index	0	0	0	0	0
Russell 1000 Comprehensive Factor Index	1	1	1	1	1

NOTES: The cyclical factor portfolio refers to the Russell 1000 2Size/2Value 5% capped total return index, and the defensive factor portfolio refers to the Russell 1000 2Quality/2 Low Volatility 5% capped total return index. The Russell 1000 Comprehensive Factor Index refers to a static, equally tilted multifactor portfolio.

SOURCE: FTSE Russell.

The dependent variable S_t is constructed using monthly returns for the S&P 500 and S&P 500 GICS® sectors, sourced from Bloomberg, for the September 1989–July 2022 time period. The cyclical factor portfolio CFP_t is constructed using FTSE Russell multifactor indexes, which use the standard FTSE Russell tilt-tilt methodology—a bottom-up sequential or "multiplicative" tilting process whereby each security's market cap weight is multiplied by the security's factor scores to reweight a portfolio toward intended factor exposures (FTSE Russell 2017). The cyclical "value & size" portfolio and the defensive "quality & low volatility" portfolio are represented by the FTSE Russell multifactor indexes in Exhibit 3, where a "2" tilt indicates a security market cap weight is multiplied by the factor score twice and a "0" indicates that the factor is not targeted.[5] For reference only, we include corresponding tilts for the Russell 1000 Index, carrying a "0" tilt to each factor, and the Russell 1000 Comprehensive Factor Index, a static multifactor benchmark with a single tilt to each factor.

RESULTS

Exhibit 4, Panels A and B, reports the output of this factor-based economic classification methodology.[6] The cyclical/defensive composition of the S&P 500 has experienced meaningful changes over the past 30 years, with cyclical sectors representing a maximum of 61% of the S&P 500 in 2014 and only 22% in 2020. Conversely, defensive sectors represented only 14% of the S&P 500 in 2008 and more than 60% between 2020–2022. Results at the individual GICS® sector level reveal the time-varying cyclicality of most sectors and, at the same time, confirm the stable economic sensitivity of some sectors. Financials, industrials, and materials screen as cyclical 100% of the time, while health care screens as defensive 100% of the time. Similarly, consumer discretionary emerges as cyclical in over 90% of the sample. These results are in line with MSCI classification and, except for industrials, also with Morningstar's classification.

[5] Polk, Haghbin, and de Longis (2020) documented how these cyclical and defensive factor portfolios had the predicted exposures to cash-flow news of 1.09 and 0.74, respectively, from July 1980–June 2018, with their difference being statistically significant.

[6] Starting in September 1999, 10-year rolling regressions are used to obtain economic sector sensitivities over the approximate length of a business cycle. To obtain more out-of-sample data, at the beginning of the sample, a 5-year regression is used (September 1989–September 1994), expanding until a 10-year window is reached in September 1999.

EXHIBIT 4A

Share of S&P 500 Market Capitalization by Economic Sector Classification

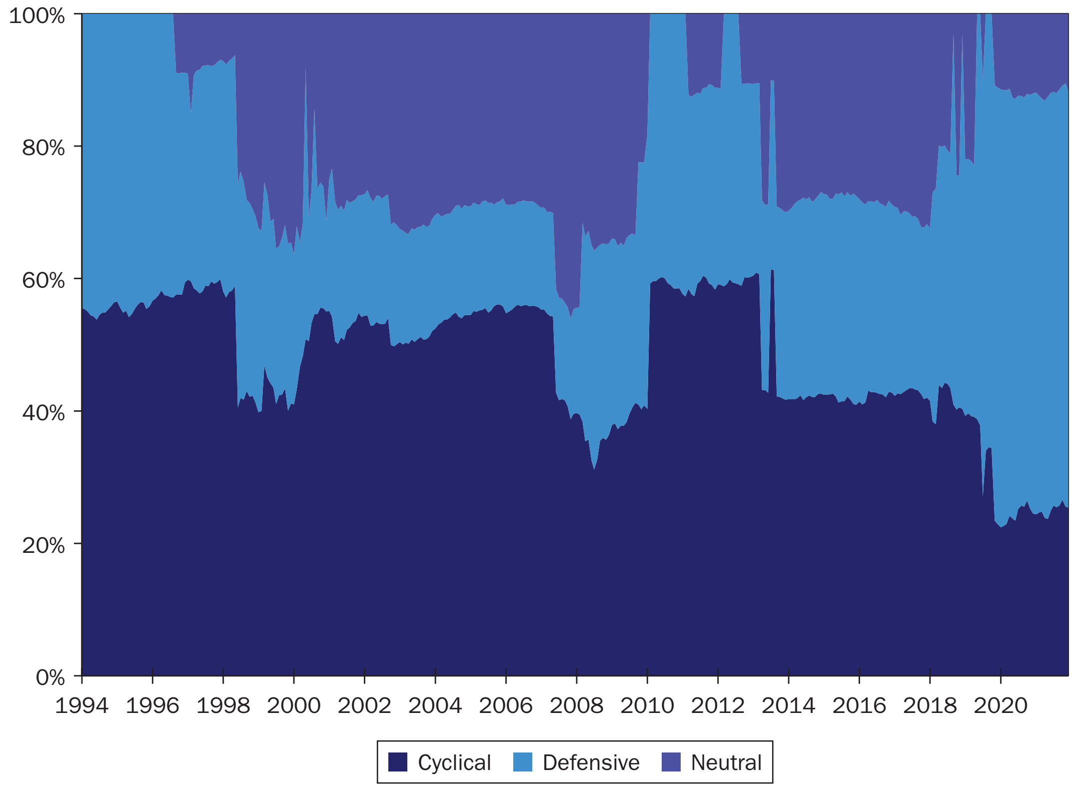


EXHIBIT 4B

Frequency of Factor-Based Classification by Sector

GICS® Sectors	Cyclical	Defensive	Neutral
S&P Consumer Discretionary	92%	0%	8%
S&P Consumer Staples	0%	71%	29%
S&P Energy	43%	16%	41%
S&P Financials	100%	0%	0%
S&P Health Care	0%	100%	0%
S&P Industrials	100%	0%	0%
S&P Information Technology	28%	11%	62%
S&P Materials	100%	0%	0%
S&P Real Estate	50%	14%	35%
S&P Communication Services	0%	99%	1%
S&P Utilities	29%	60%	12%

NOTES: September 1994–July 2022. Real estate sector data have been available since November 2001. Sample is dictated by data availability. Cyclical/defensive/neutral sector classification is based on rules outlined in Exhibit 2. Percentages may not add to 100% due to rounding. Past performance is not indicative of future results.

SOURCES: Bloomberg, S&P, FTSE Russell, and authors' calculations.

Other results are noteworthy, however. Utilities and consumer staples, commonly deemed defensive sectors, fall under the defensive classification only 60%–70% of the time, with utilities even screening as cyclical in nearly 30% of the sample. Real estate, generally classified as cyclical, screens as cyclical only 50% of the time and defensive in 14% of the sample. Communication services are categorized as defensive in nearly 100% of the observations, in sharp contrast with the cyclical and sensitive classifications from MSCI and Morningstar, respectively. Energy, a defensive sector under MSCI, screens as cyclical in over 40% of observations, defensive only 16% of the time, and neutral otherwise. Information technology, a cyclical sector under MSCI, appears cyclical less than 30% of the time and defensive 11% of the time and exhibits nonstatistically significant exposure to the cycle in approximately 62% of the past 30 years. Our results for energy and information technology seem more consistent with the "sensitive" super sector classification from Morningstar.

The time-varying cyclicality of sectors is further illustrated in Exhibit 5 where sector betas to the cyclical factor portfolio are shown with periods of low statistical significance highlighted. Analysis of a few historical periods is insightful, linking these sector classifications to some distinguished market environments of the past 30 years. The energy sector exhibited clear cyclicality between 2000–2007, a period overlapping with the commodity supercycle, and defensive characteristics for a brief period between 2010–2013, returning to an all-time high cyclicality between 2019–2022. Information technology is classified as "neutral" for about 60% of the time, including during the run-up and bursting of the dot-com bubble in 1999–2001. It assumed cyclical properties between 2010–2013 and turned into a defensive sector between 2020–2022, when technology services provided the "stay-home" solution during worldwide COVID lockdowns. In contrast, sectors such as industrials and materials have exhibited stable cyclical behavior over the past 30 years, consistent with the structurally high operating leverage of their industries.

Using this factor-based dynamic classification, we construct cyclical and defensive sector baskets, aggregated on a market-cap-weighted basis, and investigate whether they exhibit differentiated returns in different growth environments. We implement the macro regime framework of de Longis and Ellis (2023) and Polk, Haghbin, and de Longis (2020), who documented differentiated performance for equity factors, equity, credit, and term premiums between regimes. The framework combines leading economic indicators and global risk appetite to identify predictive stages of the business cycle for the US economy (recovery, expansion, slowdown, and contraction). Exhibit 6, Panels A and B, reports the relative performance between the cyclical and defensive basket and the performance of each basket relative to the market-cap index, conditional on information available at that point in time, rebalanced monthly. For brevity of exposition, regimes of accelerating growth (recovery, expansion) and decelerating growth (slowdown, contraction) are grouped together.

Results are directionally consistent with expectations. Cyclicals tend to outperform defensives in regimes of accelerating growth, with excess returns of 7.72% and a statistically significant information ratio of 0.64. Conversely, cyclicals tend to underperform defensives in regimes of decelerating growth, with annualized excess returns of –5.07% and an information ratio of –0.42, just shy of statistical significance at the 90% confidence level. Relative to the market-cap index, the defensive basket exhibits statistically significant excess returns, with the predicted sign, in both accelerating (–4.91%) and decelerating (+4.22%) growth regimes. Excess returns for the cyclical basket are directionally consistent in both growth regimes, but not statistically significant. The defensive basket exhibits higher tracking error to the market compared to the cyclical basket, with excess return volatility around 8% vs. 6.5% for the cyclical basket. These high-level results provide some evidence of differentiated performance between the two baskets and are directionally consistent with economic intuition.

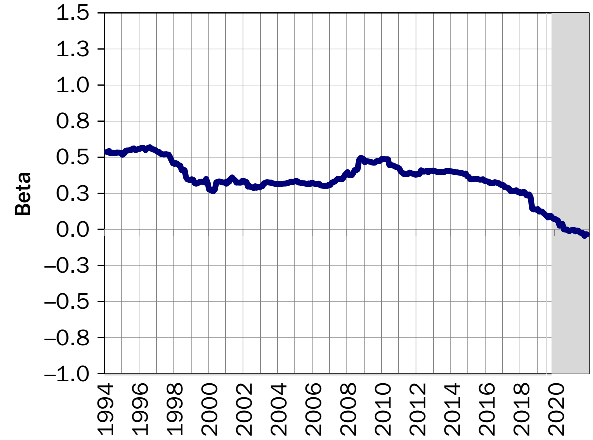
In more detail, we investigate the relative performance of each GICS® sector conditional on its factor-based cyclical/defensive classification and the predicted macro regime. As summarized in Exhibit 7, if sector S_i is classified as "cyclical" at time t, we go long (short) the sector relative to the defensive basket in an accelerating

EXHIBIT 5

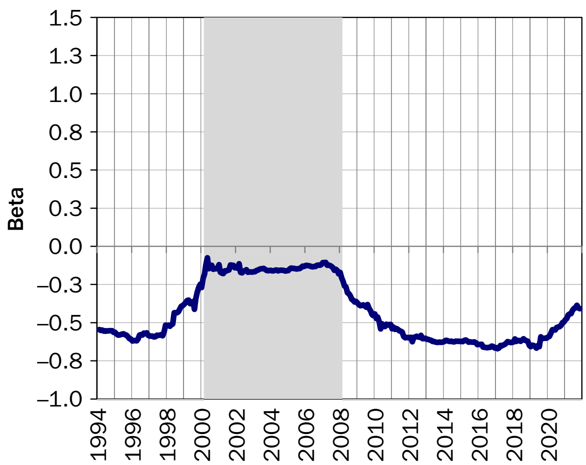
Factor-Based Economic Classification of Sectors

Sector Classification	β	p-Value	Economic Interpretation
Cyclical	> 0	≤ 0.1	Excess returns are positively correlated with cyclical factors
Neutral	any	> 0.1	Excess returns are uncorrelated with cyclical factors
Defensive	< 0	≤ 0.1	Excess returns are negatively correlated with cyclical factors

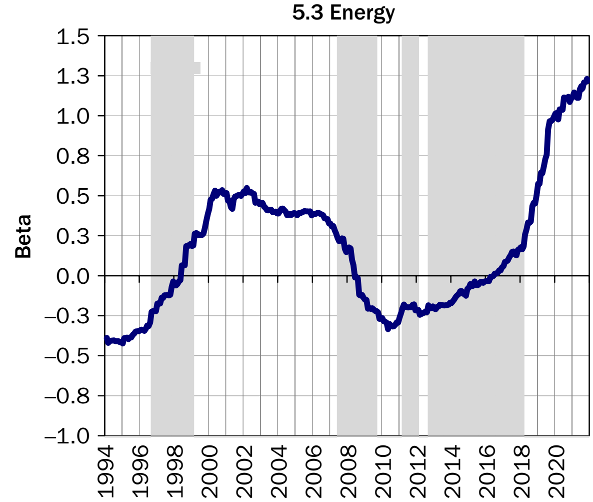
5.1 Consumer Discretionary



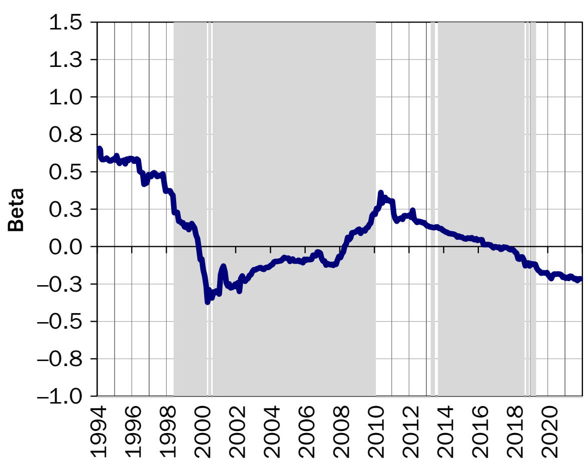
5.2 Consumer Staples



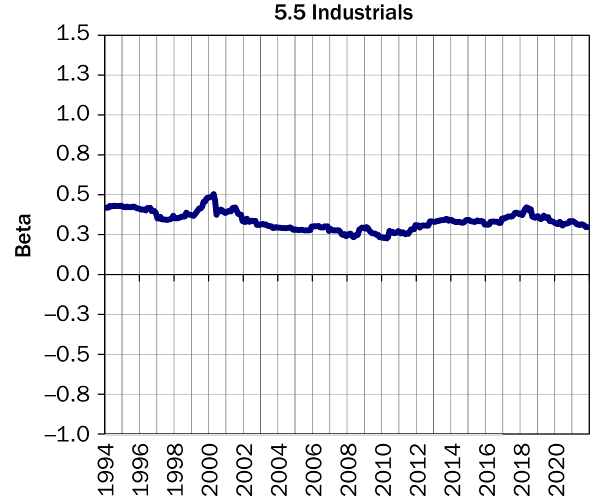
5.3 Energy



5.4 Information Technology



5.5 Industrials

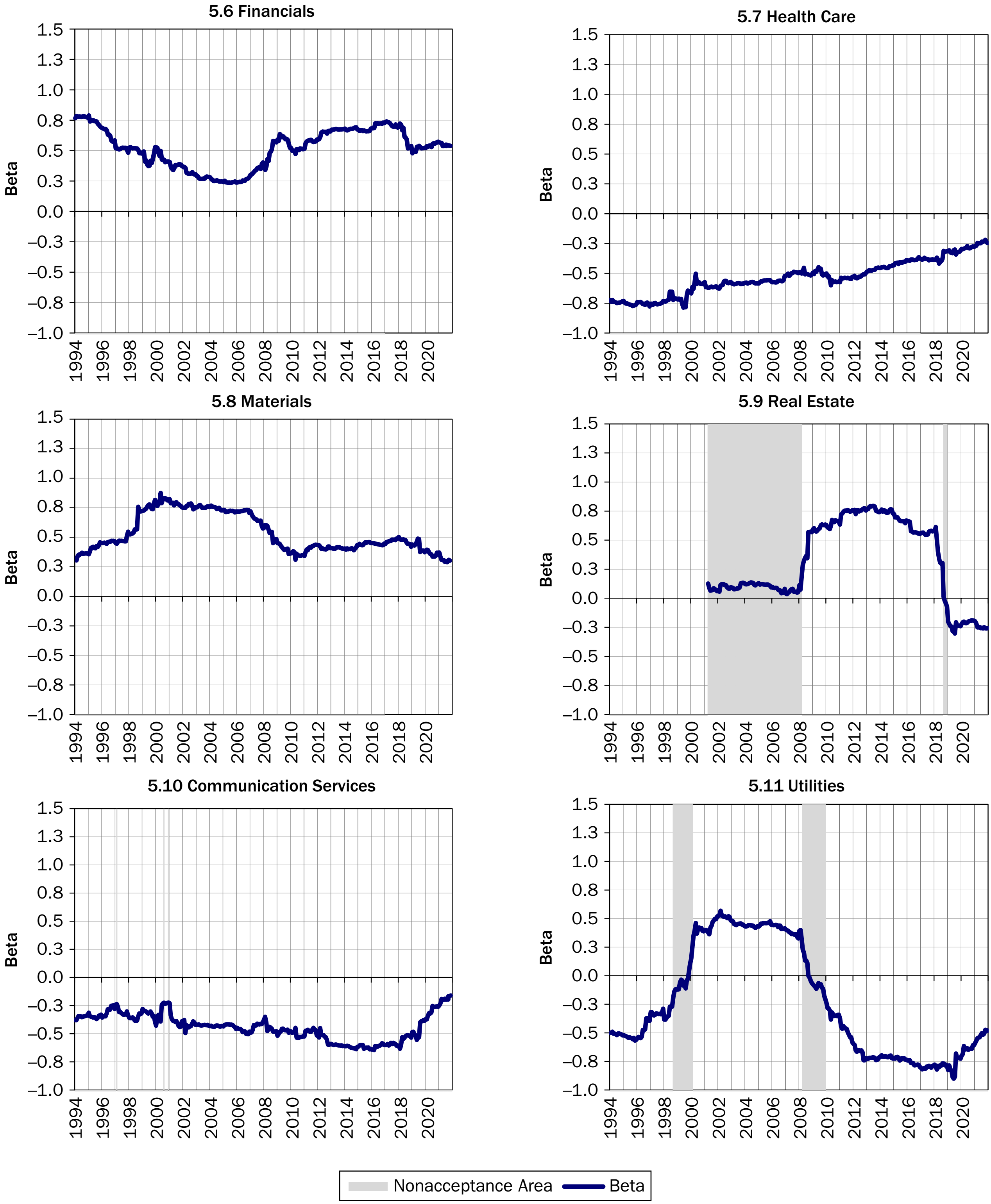


Nonacceptance Area — Beta

(continued)

EXHIBIT 5 *(continued)*

Factor-Based Economic Classification of Sectors



NOTES: A p-value of ≤ 0.1 denotes significance with 90% confidence interval or higher. Nonacceptance areas in graphs 5.1–5.11 indicate periods when the p-value is > 0.10 and the beta is nonstatistically significant. September 1989–July 2022, dictated by data availability. The cyclical/defensive sector classification is based on rules outlined in Exhibit 2. Nonacceptance area indicates periods where the p-value is > 0.10 and the beta is statistically nonsignificant.

SOURCES: Bloomberg, S&P, and FTSE Russell.

EXHIBIT 6A

Relative Performance of Cyclical and Defensive Baskets, by Growth Regime

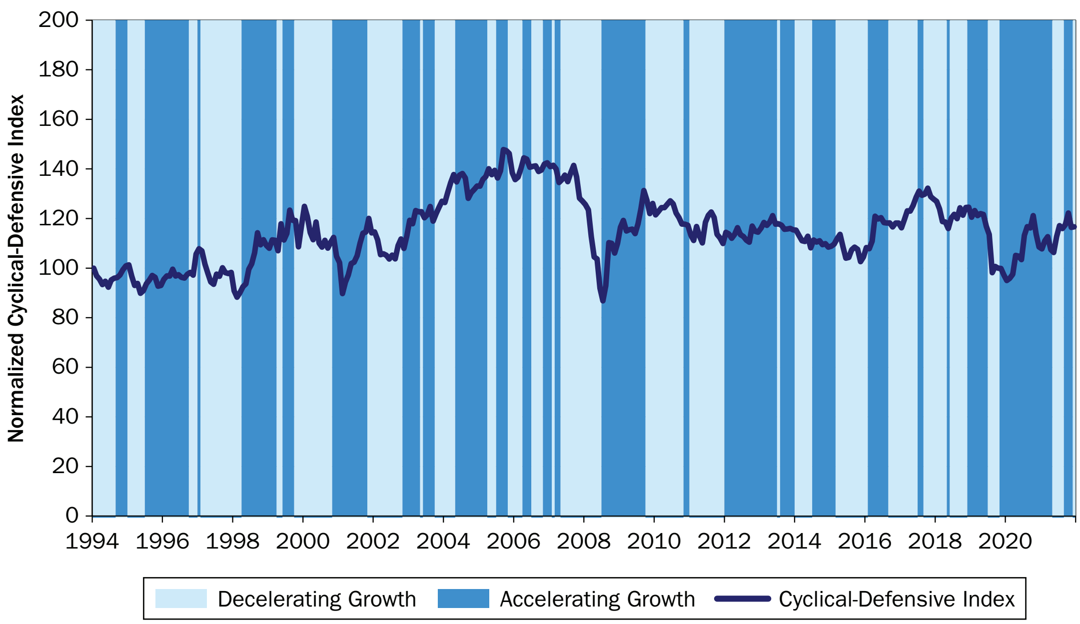
	As of July 31, 2022								
	Full Sample			Accelerating Growth			Decelerating Growth		
	Cyclical–Defensive	Cyclical–Market Index	Defensive–Market Index	Cyclical–Defensive	Cyclical–Market Index	Defensive–Market Index	Cyclical–Defensive	Cyclical–Market Index	Defensive–Market Index
Annualized Returns	1.28%	0.97%	–0.31%	7.72%**	2.81%	–4.91%**	–5.07%	–0.84%	4.22%*
Volatility	12.18%	6.55%	8.30%	12.07%	6.48%	7.89%	12.04%	6.60%	8.52%
Information Ratio	0.11	0.15	–0.04	0.64	0.43	–0.62	–0.42	–0.13	0.50
Skewness	0.21	0.21	0.00	0.71	1.32	0.31	–0.27	–0.81	–0.31
Kurtosis	3.16	6.32	3.09	4.53	6.70	4.27	1.61	5.68	2.92
P-value	0.58	0.43	0.84	0.02	0.11	0.02	0.12	0.63	0.06
Obs. (# months)	336	336	336	167	167	167	169	169	169

NOTES: September 1994–July 2022, dictated by data availability. The cyclical/defensive sector classification is based on rules outlined in Exhibit 2. *, **, and *** denote rejection of the null hypothesis that returns are equal to zero for a two-tailed p-value at the 10%, 5%, and 1% significance levels, respectively.

SOURCES: Bloomberg, S&P, FTSE Russell, and authors' calculations. Past performance is not indicative of future results.

EXHIBIT 6B

Cyclical-Defensive Index and Growth Regime



NOTES: September 1994–July 2022, dictated by data availability. The cyclical/defensive sector classification is based on rules outlined in Exhibit 2. Accelerating/decelerating growth regimes are defined as in de Longis and Ellis (2023) and Polk, Haghbin, and de Longis (2020).

SOURCES: Bloomberg, S&P, and FTSE Russell.

EXHIBIT 7

Sector Rotation Strategy Conditional on Growth Regime

IF Sector $S_{i,t}$	Accelerating Growth$_t$	Decelerating Growth$_t$
Cyclical	($S_{i,t+1}$ – Defensives$_{t+1}$)	(Defensives$_{t+1}$ – $S_{i,t+1}$)
Neutral	N/A	N/A
Defensive	(Cyclicals$_{t+1}$ – $S_{i,t+1}$)	($S_{i,t+1}$ – Cyclicals$_{t+1}$)

(decelerating) growth regime; conversely, if sector S_i is classified as "defensive" at time t, we go long (short) the sector relative to the cyclical basket in a decelerating (accelerating) growth regime.

Sector-level results are reported in Exhibit 8 and, for reference only, compared to results obtained using the static MSCI classification from Exhibit 2. For the dynamic factor-based model, 10 out of 11 sectors delivered positive excess returns on a full sample basis, with statistically significant results in 7 sectors, or 64% of the panel. Energy is the only sector delivering negative returns, but they are statistically insignificant. All 11 sectors delivered positive excess returns in an accelerating growth environment, and 9 out of 11 sectors delivered positive excess returns in a decelerating growth environment. Statistical significance in these two subsamples is reduced due to the smaller number of observations.

Financials, healthcare, industrials, and materials, where a factor-based classification aligns 100% of the time with the static alternative, all deliver positive excess returns in the full sample and within each growth regime. Consumer discretionary could be added to this group, given a 92% overlap with the static cyclical classification. Results are statistically significant, except for materials. The most interesting results emerge with communication services, information technology, and consumer staples, whereby as illustrated in Exhibit 4, our factor-based classifications are meaningfully different from the respective static classifications. Excess returns are statistically significant for all three sectors, with positive returns in both accelerating and decelerating growth regimes.

Furthermore, these results outperform the excess returns generated by the static alternative in Panel B of Exhibit 8, highlighting the incremental value of a factor-based dynamic classification. Notably, communication services are deemed defensive in

EXHIBIT 8A

Sector Rotation Strategy with Factor-Based Economic Classification

	Full Sample				Accelerating Growth				Decelerating Growth			
S&P 500 GICS® Sectors	Excess Returns	Vol.	IR	Obs.	Excess Returns	Vol.	IR	Obs.	Excess Returns	Vol.	IR	Obs.
Consumer Disc.	5.53%**	12.68%	0.44	310	7.76%**	12.95%	0.60	147	3.52%	12.44%	0.28	163
Consumer Staples	9.4%***	14.80%	0.64	240	12.26%***	14.61%	0.84	122	6.45%	15.01%	0.43	118
Energy	–1.07%	21.97%	–0.05	199	5.57%	22.01%	0.25	105	–8.50%	21.86%	–0.39	94
Financials	9.52%***	15.68%	0.61	336	9.32%**	14.61%	0.64	167	9.72%**	16.71%	0.58	169
Health Care	6.32%**	14.45%	0.44	336	5.10%	13.98%	0.37	167	7.52%*	14.94%	0.50	169
Industrials	4.92%**	12.49%	0.39	336	5.35%	12.56%	0.43	167	4.51%	12.46%	0.36	169
Info. Technology	10.61%*	18.74%	0.57	129	12.85%*	17.86%	0.72	66	8.26%	19.73%	0.42	63
Materials	3.96%	16.48%	0.24	336	3.19%	16.17%	0.20	167	4.73%	16.83%	0.28	169
Real Estate	3.00%	16.60%	0.18	160	5.20%	19.24%	0.27	84	0.57%	13.19%	0.04	76
Comm. Services	7.17%**	17.40%	0.41	333	11.84%***	15.17%	0.78	166	2.53%	19.32%	0.13	167
Utilities	2.87%	18.06%	0.16	297	7.46%	17.70%	0.42	142	–1.33%	18.35%	–0.07	155

EXHIBIT 8B

Sector Rotation Strategy with Static Economic Classification

	Full Sample				Accelerating Growth				Decelerating Growth			
S&P 500 GICS® Sectors	Excess Returns	Vol.	IR	Obs.	Excess Returns	Vol.	IR	Obs.	Excess Returns	Vol.	IR	Obs.
Consumer Disc.	4.93%**	12.68%	0.39	336	6.31%*	12.63%	0.50	167	3.56%	12.76%	0.28	169
Consumer Staples	4.97%*	14.30%	0.35	336	5.94%	13.92%	0.43	167	4.00%	14.71%	0.27	169
Energy	4.38%	17.39%	0.25	336	4.65%	17.14%	0.27	167	4.12%	17.68%	0.23	169
Financials	9.52%***	15.68%	0.61	336	9.32%**	14.61%	0.64	167	9.72%**	16.71%	0.58	169
Health Care	6.32%**	14.45%	0.44	336	5.10%	13.98%	0.37	167	7.52%*	14.94%	0.50	169
Industrials	4.92%**	12.49%	0.39	336	5.35%	12.56%	0.43	167	4.51%	12.46%	0.36	169
Info. Technology	7.65%**	20.20%	0.38	336	13.24%**	19.01%	0.70	167	2.12%	21.24%	0.10	169
Materials	3.96%	16.48%	0.24	336	3.19%	16.17%	0.20	167	4.73%	16.83%	0.28	169
Real Estate	2.43%	17.11%	0.14	249	2.65%	17.30%	0.15	126	2.21%	16.99%	0.13	123
Comm. Services	–1.01%	13.11%	–0.08	336	–4.28%	11.43%	–0.38	167	2.20%	14.56%	0.15	169
Utilities	7.71%**	18.46%	0.42	336	9.84%*	18.74%	0.53	167	5.61%	18.21%	0.31	169

NOTES: September 1994–July 2022, sample dictated by data availability. Strategy rebalancing rules are outlined in Exhibit 7. Average annualized excess returns. IR stands for Information Ratio. *, **, and *** denote rejection of the null hypothesis that returns are equal to zero for a two-tailed p-value at the 10%, 5%, and 1% significance levels, respectively.

SOURCES: Bloomberg, S&P, MSCI, FTSE Russell, and authors' calculations. Past performance is not indicative of future results.

99% of observations and delivered statistically significant outperformance with +7.17% annual returns, which is in sharp contrast to the negative returns generated by the static "cyclical" classification. For consumer staples, a static "defensive" classification would have produced about +5% annual excess returns, compared to the dynamic factor-based rule generating +9.4% excess returns, also statistically significant. This outperformance occurred in both accelerating and decelerating regimes, confirming the benefits emerging from the 30% of observations when the sector was classified as "neutral." For information technology, a static "cyclical" classification would have produced about +7.65% annual excess returns over the full sample, compared to the dynamic factor-based rule generating +10.61% excess returns, statistically significant, in the 38% of observations when the sector was classified as either cyclical or defensive. This relative outperformance confirms the sector exhibited weaker cyclicality in the 62% of observations when classified as neutral. For real estate, results are positive but insignificant, in line with the static classification alternative. Finally, the factor-based classification rule underperforms the static alternatives for energy and utilities. For energy, the static "defensive" classification delivers positive but insignificant returns over the full sample and in each growth regime. In contrast, the dynamic classification rule delivers negative returns, on average, over the entire period. For utilities, our results are marginally positive and statistically insignificant, but clearly underperform the static "defensive" classification alternative that generated positive and significant returns of 7.71%.

APPLICATION EXAMPLE: SECTOR ROTATION STRATEGY

Considering these broadly positive results, we document a simple and practical sector rotation strategy, easily implementable by both retail and institutional investors via liquid and cost-effective sector ETFs or index funds. The strategy seeks

EXHIBIT 9

US Sector Rotation Strategy Example

	Factor-Based Economic Classification			Static Economic Classification		
Sector Rotation Strategy	**Full Sample**	**Accelerating Growth**	**Decelerating Growth**	**Full Sample**	**Accelerating Growth**	**Decelerating Growth**
Annualized Returns	12.17%	12.85%	11.48%	11.92%	12.78%	11.06%
Standard Deviation	14.93%	14.10%	15.75%	14.90%	14.25%	15.56%
Return–Risk Ratio	0.82	0.91	0.73	0.80	0.90	0.71
Excess Returns	1.32%***	1.25%**	1.39%**	1.07%**	1.18%**	0.97%
Tracking Error	2.27%	2.04%	2.49%	2.32%	2.06%	2.55%
Information Ratio	0.58	0.62	0.56	0.47	0.57	0.38
Skewness	0.94	1.11	0.82	0.07	0.37	–0.08
Kurtosis	4.50	4.98	4.00	1.32	1.79	0.89
S&P 500 Index						
Annualized Returns	10.84%	11.60%	10.09%	10.84%	11.60%	10.09%
Standard Deviation	15.13%	13.12%	16.93%	15.13%	13.12%	16.93%
Return–Risk Ratio	0.72	0.88	0.60	0.72	0.88	0.60

NOTES: September 1994–July 2022, sample dictated by data availability. Strategy rebalancing rules are outlined in Exhibit 7. *, **, and *** denote rejection of the null hypothesis that returns are equal to zero for a two-tailed p-value at the 10%, 5%, and 1% significance levels, respectively.

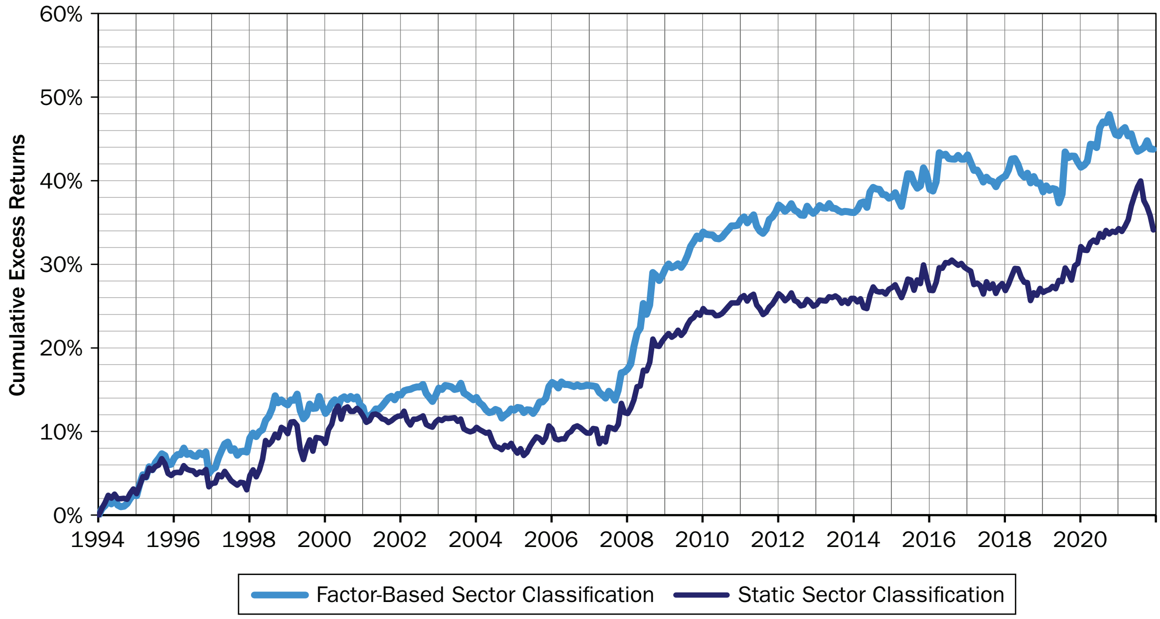
SOURCES: Bloomberg, S&P, MSCI, FTSE Russell, and authors' calculations. Past performance is not indicative of future results.

to outperform the market-cap index by repositioning the portfolio toward sectors expected to outperform in each macro regime, based on their cyclical characteristics. Several risk budgeting and portfolio construction rules can be used to implement this strategy, but extensive analysis of these alternatives is beyond the scope of this article. To keep the illustration simple, practical, and unbiased to portfolio construction alternatives, we opt for a simple tracking error budgeting rule. On a monthly basis, conditional on the predicted growth regime, we sell the sector-basket expected to underperform to fund the overweight exposure in the sector-basket expected to outperform, with the sizing of the position calibrated to a 2% trailing three-year tracking error. For simplicity, within each cyclical and defensive basket, sectors are weighted in proportion to their market caps, therefore indifferent to the estimated magnitude of their cyclicality.[7] Finally, sectors classified as "neutral" are held at their market cap weight, hence neutral to the benchmark.

Results are reported in Exhibits 9 and 10, where this hypothetical strategy is benchmarked against the market-cap index and compared to the static classification alternative. The factor-based sector rotation strategy delivers attractive excess returns of about 1.32%, with a statistically significant information ratio of 0.58. Results are consistent and significant in both accelerating and decelerating growth regimes. By alternating between cyclical and defensive exposures over time, this outperformance is not generated by taking more risk than the benchmark over the entire sample. As expected, strategy volatility is higher than benchmark volatility during accelerating growth regimes when the strategy assumes a cyclical stance (14.10% vs. 13.12%), and lower than the benchmark when the strategy assumes a defensive stance (15.75% vs. 16.93%). The distribution of excess returns also exhibits attractive positive skewness of 0.94. This strategy also compares favorably to the results generated using the static classification alternative, with a marginal

[7] This is an area for future research, where the estimated magnitude of sector cyclicality could inform portfolio weighting schemes.

EXHIBIT 10
US Sector Rotation Strategy



NOTES: September 1994–July 2022, sample dictated by data availability. Strategy rebalancing rules are outlined in Exhibit 7.

SOURCES: Bloomberg, S&P, MSCI, FTSE Russell, and authors' calculations. Past performance is not indicative of future results.

improvement in information ratio from 0.47 to 0.58. This improvement is more evident during decelerating growth regimes, where the information ratio improves from 0.38 to a statistically significant 0.56, and the skewness in excess returns also improves from –0.08 to 0.82. For robustness, we reproduce the methodology for global equity sectors, regressed against the corresponding global cyclical factor portfolio, and obtain very similar results, which are reported in the appendix.

CONCLUSION

Factor investing is founded on the explicit recognition that factors are important drivers of portfolio risk and performance, representing more-relevant characteristics of a security than its country, sector, or industry classification. Factor cyclicality can shed light on the fundamental characteristics of traditional assets and also support allocation decisions among market-cap-weighted asset classes or sectors. We propose a simple and practical methodology to classify sectors as cyclical or defensive by estimating sector sensitivity to a cyclical multifactor portfolio and delivering a more dynamic sector classification process that captures the inherent time-varying fundamentals of sectors and industries. We document the effectiveness of this factor-based economic classification and provide examples of sector rotation strategies that have historically generated attractive excess returns with information ratios between 0.50–0.60, thus outperforming static sector classification alternatives. Opportunities for future work include analysis and ranking of sector cyclicality based on ex ante factor metrics, complementary to the ex post return-based style analysis proposed here.

APPENDIX

EXHIBIT A1

Global Sector Rotation Strategy Example

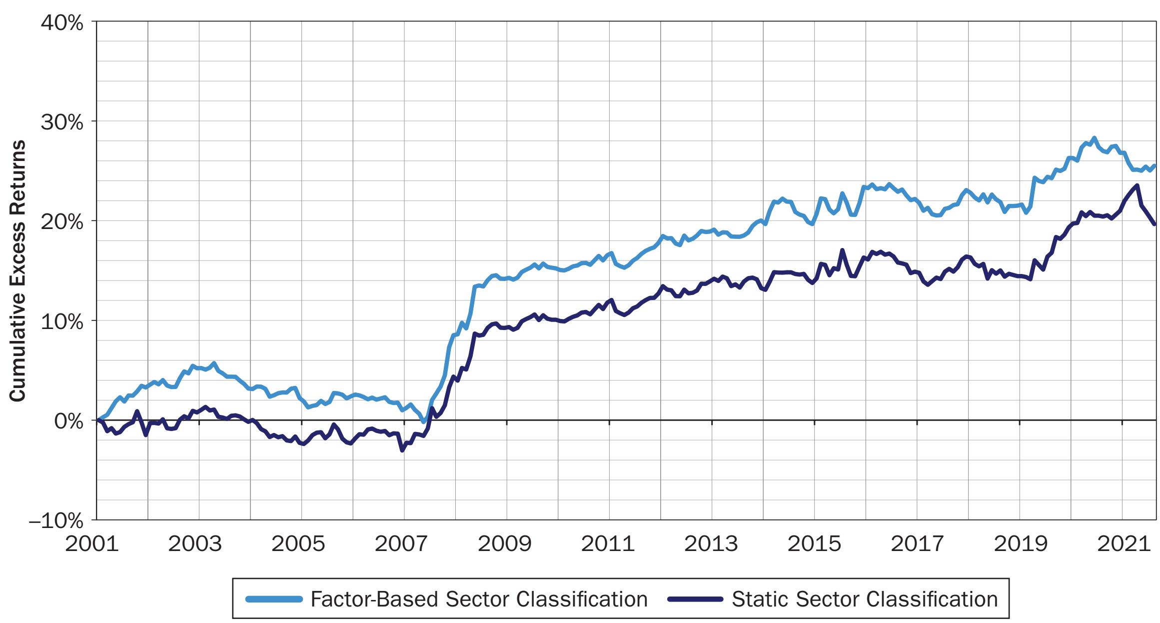
	Factor-Based Economic Classification			Static Economic Classification		
Global Sector Rotation Strategy	**Full Sample**	**Accelerating Growth**	**Decelerating Growth**	**Full Sample**	**Accelerating Growth**	**Decelerating Growth**
Annualized Returns	9.73%	13.26%	6.18%	9.45%	12.83%	6.04%
Standard Deviation	15.28%	13.70%	16.72%	15.36%	13.83%	16.75%
Return–Risk Ratio	0.64	0.97	0.37	0.62	0.93	0.36
Excess Returns	1.23%***	1.30%**	1.17%*	0.95%**	0.87%	1.03%
Tracking Error	2.09%	1.85%	2.31%	2.11%	1.90%	2.32%
Information Ratio	0.59	0.70	0.51	0.45	0.46	0.45
Skewness	1.25	1.15	1.29	0.30	0.18	0.35
Kurtosis	4.12	4.24	3.80	1.82	3.63	0.80
MSCI ACWI Index						
Annualized Returns	8.50%	11.96%	5.00%	8.50%	11.96%	5.00%
Standard Deviation	15.63%	12.71%	18.11%	15.63%	12.71%	18.11%
Return–Risk Ratio	0.54	0.94	0.28	0.54	0.94	0.28

NOTES: December 1994–July 2022, sample dictated by data availability. Strategy rebalancing rules are outlined in Exhibit 7 for the MSCI ACWI Index. Backtest sample is from January 2002–July 2022. Global business cycle regimes are used in place of US cycle regimes, and the global cyclical factor portfolio is constructed as the market-cap-weighted average of the R1000, FTSE Developed ex-US, and FTSE EM factor portfolios, following the same rules outlined in Exhibits 2 and 3. *, **, and *** denote rejection of the null hypothesis that returns are equal to zero for a two-tailed p-value at the 10%, 5%, and 1% significance levels, respectively.

SOURCES: Bloomberg, MSCI, FTSE Russell, and authors' calculations. Past performance is not indicative of future results.

EXHIBIT A2

Global Sector Rotation Strategy



NOTES: December 1994–July 2022, sample dictated by data availability. Backtest sample is from January 2002–July 2022. Strategy rebalancing rules are outlined in Exhibit 7 for the MSCI ACWI Index.

SOURCES: Bloomberg, MSCI, FTSE Russell, and authors' calculations. Past performance is not indicative of future results.

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Hypothetical simulated performance

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